

SOWA Method Framework: New Algorithm for Criteria Weight Balancing with a Hybrid Subjective and Objective Approach

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Abstract: This research proposes the implementation of the subjective and objective weighting approach (SOWA) method as a new approach in determining the criteria weights that combines subjective assessments from experts and data-driven objective calculations. The criteria weights generated from the SOWA method are then used in various multi-criteria decision-making (MCDM) methods, such as simple additive weighting (SAW), technique for order preference by similarity to ideal solution (TOPSIS), multi-objective optimization on the basis of ratio analysis (MOORA), grey relational analysis (GRA), multi-attribute utility theory (MAUT), weighted aggregated sum product assessment (WASPAS), weighted product (WP), simple multi-attribute rating technique (SMART), multi-attribute border approximation area comparison (MABAC), and Multi-Attributive Ideal-Real Comparative Analysis (MAIRCA), to evaluate and rank alternatives. The research results show that the SOWA method is capable of producing balanced and representative weights, as well as consistent alternative rankings across MCDM methods. Sensitivity analysis of the ranking results indicates that the rankings remain stable across weight scenarios, signifying a high level of stability and reliability of the generated weights. These findings demonstrate that the SOWA method can serve as a solid foundation in decision support systems, particularly in the context of candidate selection or evaluation based on multiple criteria.

Index Terms: MCDM, New Approach, Objective, SOWA Method, Subjective

1. Introduction

Multi-criteria decision making (MCDM) plays a crucial role in various fields because it allows for more comprehensive and rational decision making amidst the complexity of problems involving multiple aspects or criteria[1-3]. By simultaneously considering various factors, MCDM helps decision-makers not only to focus on one aspect but also to formulate comprehensive and fair solutions in accordance with the strategic goals they wish to achieve. Accuracy is a crucial element in MCDM systems as it determines the quality and reliability of the final results of the decision-making process. In the context of MCDM, each alternative is evaluated based on various criteria that have different weights and levels of importance[4-6]. Inaccuracies in determining the weights of criteria, measuring data, or calculation methods can lead to decision results that deviate from real conditions and risk producing suboptimal or even incorrect decisions. High accuracy ensures that every important aspect of the problem is considered appropriately and proportionally, resulting in rational, objective, and accountable decisions. Therefore, data integrity, the selection of appropriate methods, and thorough validation of results are important factors in maintaining accuracy in MCDM systems.

One of the main issues in MCDM is the sensitivity of decision outcomes to the determination of criterion weights. Criterion weights reflect the relative importance of each evaluated aspect and therefore play a central role in influencing the final results of the decision-making process[7,8]. When weights are determined subjectively or without appropriate methods, the results obtained can be biased, inconsistent, or even misleading. In many cases, small changes in criterion weights can result in significant differences in the ranking order of alternatives, leading to uncertainty and reducing the reliability of decisions[9-11]. This issue becomes increasingly complex when decisions must be made under uncertainty or when the criteria being considered have different units and scales. Therefore, the selection of the appropriate weighting determination method becomes very important[12]. Ideally, the approach used should be able to capture the complexity of the relationships between criteria and minimize the subjectivity of the decision-maker[13-15]. To enhance accuracy, validation processes, sensitivity analyses, and hybrid approaches between subjective and objective methods are often employed. Thus, accuracy in weight determination is an important prerequisite for the successful implementation of a fair and reliable MCDM system.

In MCDM, there are three main approaches to determining criterion weights, namely subjective, objective, and ranking-based approaches. The subjective approach relies on the intuition, experience, and preferences of experts[5,16-17], with methods such as AHP, SMART, and Delphi, which are capable of capturing qualitative aspects and strategic values. However, this approach is susceptible to bias and inconsistency. Conversely, the objective approach uses data-driven methods such as Entropy, CRITIC, and LOPCOW that generate weights automatically, free from human intervention, and offer high consistency, although it is less able to capture context and non-quantitative considerations[17-19]. Ranking-based approaches are in the middle ground, where decision-makers are only asked to rank the criteria without directly assigning weight values. Methods such as ROC, Rank Sum, and SMARTER offer simplicity and ease of use, yet still contain subjective elements and lack precision in capturing the strength of preferences between criteria[20]. These three approaches can be used separately or combined in a hybrid approach to balance data accuracy, decision context, and ease of implementation. The choice of the right approach highly depends on the complexity of the problem, data availability, as well as the preferences and capabilities of the decision-makers.

The subjective method in determining weights or assessing criteria is often used because it can capture intuition, experience, and deep expertise in a specific domain[21,22]. The accuracy of this method lies in its ability to describe nuances and specific contexts that may not be reached by objective approaches alone. However, the subjective method has a main drawback, being vulnerable to personal bias. Individual preferences, past experiences, or even unconscious perceptions can influence assessment outcomes, thereby reducing consistency and fairness.

The objective data-based method is an approach in decision-making that utilizes quantitative information mathematically and statistically to determine the weight or value of a criterion[23-25]. The main advantage of this method lies in its consistency, neutrality, and freedom from the influence of subjectivity, as the entire analysis process is conducted automatically based on the available data. However, a significant drawback of the objective method is its tendency to overlook intuition, contextual knowledge, and the values of expertise, which are often important in real-world decision-making. Therefore, although the objective method can provide logical and measurable results, its exclusive use without considering input from experts can lead to decisions that are less relevant or not entirely aligned with the actual conditions in the field.

The weighting of criteria in an MCDM system plays a very important role because it helps reflect the relative importance level of each criterion used in the decision-making process[26-28]. In real situations, not all criteria have the same influence on the final outcome, so assigning weights allows the system to adjust the calculations proportionally based on the contribution of each criterion. Without weighting, all criteria would be considered equally important, which could lead to less accurate or even misleading decisions. Weighting also helps decision-makers focus more on aspects deemed crucial, as well as enhances objectivity and transparency in evaluating alternatives[29-31]. Therefore, an appropriate weighting process is crucial for the quality and validity of the final results in MCDM methods.

1.1. Research Problem

Dependence on a single weighting approach in MCDM can lead to imbalances and inaccuracies in evaluation results. This is because each weighting method, whether subjective or objective, has its own assumptions, advantages, and limitations. If only one method is used, the evaluation results can be excessively influenced by the perspective or characteristics of that method. Subjective methods heavily rely on the perceptions and preferences of the decision-makers, which can be biased or inconsistent. On the other hand, objective methods disregard human judgment and are based solely on data, which may not fully reflect the reality or priorities of the organization. This imbalance can result in weights that do not accurately reflect the importance of the criteria as a whole, leading to misleading outcomes in the alternative ranking process. In practical terms, this can negatively impact the selection of the best alternative, reduce trust in the system's results, and even lead to detrimental decisions. Therefore, to enhance the accuracy and reliability of the results, a hybrid approach that combines both subjective and objective methods is often recommended in MCDM criterion weighting. This approach can balance human judgment and data analysis, resulting in a more comprehensive and representative evaluation.

The issue of the imbalance between subjective perception and objective reality is a challenge often faced in MCDM systems. Subjective perception comes from the experiences, intuition, or opinions of decision-makers, while objective reality is based on measurable data and facts[32,33]. When the two are not aligned, the evaluation results can become biased or may not reflect the actual conditions. For example, a decision-maker may assign high weight to criteria that they believe are important based on personal experience, while the data shows that those criteria have a minimal impact on the success of alternatives. This imbalance can obscure the actual priorities and lead to suboptimal decisions. In a managerial context, this can affect the selection of inappropriate strategies, inefficient allocation of resources, or failure to achieve organizational goals. This issue also complicates the evaluation process because subjectivity is difficult to measure consistently, while objectivity may not capture contextually important nuances[34,35]. Therefore, it is essential to establish careful and proportional integration mechanisms between subjective perceptions and objective realities, so that the decisions made reflect a balance between human views and empirical evidence, as well as being more adaptive to the real dynamics in the field.

On the other hand, relying entirely on intuition or expert opinion also carries the risk of bias and lacks objectivity. Without a flexible mechanism to integrate both types of weights, MCDM systems tend to be rigid and unable to adapt to various decision-making contexts. Therefore, there is a need for methods or frameworks that allow for the adjustment of proportions between subjective and objective weights, such as through integrative techniques (e.g., hybrid methods) or dynamic adjustment schemes that consider the characteristics of the problem and the needs of the decision maker. Thus, the resulting decisions will be more balanced, representative, and applicable in various situations.

1.2. A New Approach to Subjective and Objective-Based Criteria Weighting

A new approach to determining criteria weights based on subjective and objective measures is a hybrid strategy that combines the strengths of expert assessments (subjective) with quantitative data analysis (objective) to generate more balanced, relevant, and accountable decisions. In this approach, initial assessments are provided by experts based on experience, intuition, and a deep understanding of the problem context, thereby capturing aspects that are not reflected in numerical data. Subsequently, objective methods are applied to analyze variation and relationships among the data, as well as to measure the actual contribution of each criterion. The results from both approaches are then normalized and combined using specific balancing factors, whether they are fixed or adaptive depending on data quality and the level of expert confidence. This approach can also be complemented by sensitivity analysis to evaluate the stability of weights against changes in input. Thus, this combined approach not only reduces subjective bias but also maintains contextual relevance and analytical accuracy, making it highly suitable for decision-making in complex and dynamic situations. In addition to its advantages in terms of balance between intuition and data, this combined approach also enhances transparency and accountability in the decision-making process. This approach is also flexible and can be adapted to various fields of application. In a dynamic environment, where conditions and priorities can change, this approach allows for more adaptive decision-making without losing methodological validity. By integrating subjective and objective dimensions in a structured manner, this approach addresses the need for a comprehensive, responsive, and analytically excellent criterion assessment method that is also grounded in practical field values.

The subjective-objective weighting approach (SOWA method) is a new approach in determining the weights of criteria that combines two main perspectives, namely subjective assessment based on the importance level of the criteria and objective analysis based on the correlation among criteria. The main goal of this method is to create a weighting system that balances expert knowledge and the strength of data analysis; thus, it can be effectively used in various contexts of multi-criteria decision making. In the subjective stage, experts or decision-makers assess the importance of each criterion based on their experience, intuition, and understanding of the context of the problem. This assessment is usually presented in the form of a preference scale or ranking, reflecting perceptions of the relative influence of each criterion on the overall objective.

Meanwhile, in the objective stage, correlation analysis among criteria is used to measure the extent to which a criterion provides unique or different information compared to other criteria. The lower the correlation of a criterion

with other criteria, the greater its contribution of information, and thus its objective weight will be higher.

After the weights from the subjective and objective aspects are obtained, both are combined using a linear combination scheme, such as a weighted average, where the proportion of contribution from the subjective and objective can be adjusted based on the user's needs or the level of trust in each source of information. Thus, the SOWA method not only relies on contextual expert intuition but also avoids information redundancy between criteria through a data-driven approach. This method is very suitable for use in conditions where expert assessments are available, but control over bias and excess or similarity of information between criteria is still necessary.

1.3. Research Contribution

The main contribution of the research proposing the SOWA method lies in the development of a hybrid approach that bridges the strengths of expert assessment and data-driven analysis in determining criterion weights. This research provides a theoretical contribution by formulating a new methodological framework that structurally and measurably integrates the importance level of criteria (subjective) and the correlation between criteria (objective). By integrating these two dimensions, this method addresses the limitations of conventional approaches that rely solely on one side—whether subjective, which is prone to bias, or objective, which often ignores context[36–38]. Furthermore, this approach enhances the accuracy and accountability of decisions by producing criterion weights that not only reflect the perceived importance of an aspect but also account for its informational contribution empirically.

This research makes several significant contributions in the field of multi-criteria decision making, particularly regarding the determination of criterion weights. The main contributions from the development of the SOWA method are as follows:

- *Development of a New Balancing Method*

This research introduces a new algorithmic framework capable of combining subjective weights (based on expert assessments) and objective weights (based on data) in a structured and proportional manner. Unlike conventional hybrid methods that combine weights using simple averages or fixed weighting, the SOWA Method adopts a flexible adjustment mechanism through dynamic integration coefficients.

- *Flexibility of Adjustment to Dominance Weighting*

The SOWA Method allows decision-makers to regulate the level of dominance between subjective and objective approaches based on context, problem complexity, and the level of trust in data sources. This makes the method more adaptive to various decision-making scenarios, whether based on historical data or expert opinions.

- *Enhancing Transparency and Accountability in Assessment*

By explicitly separating subjective and objective contributions, this method increases the transparency of the weighting determination process and facilitates the auditing process and justification of decisions. This model can support a more accountable decision-making system, especially in the context of organizations or public policies.

- *Implementation in Various Domains*

The SOWA method is designed to be implementable in various MCDM (Multi-Criteria Decision Making) methods, such as TOPSIS, MOORA, SAW, or COPRAS, providing flexibility for integration into existing decision support systems. It has potential applications in various fields, such as supply chain management, supplier selection, performance evaluation, business strategy selection, and policy prioritization.

- *Theoretical and Practical Contribution*

Theoretically, this study enriches the literature on hybrid approaches in criterion weighting. Practically, the SOWA Method provides concrete solutions for practitioners and decision-makers in facing the dilemma between data reliability and expert intuition.

2. Methodology

This research uses a quantitative methodological approach that focuses on the development and validation of a hybrid-based criteria weight determination algorithm, which combines subjective and objective sources. The methodology employed is designed to address the need for a balance of information from the level of importance of the criteria (subjective) and actual data (objective) in multi-criteria decision making.

2.1. SOWA Method Framework

The SOWA method is an algorithmic framework designed to flexibly and adaptively balance the contributions between subjective and objective weights. This framework allows for a more accurate and transparent arrangement of criteria weights by proportionally considering two main sources of information. Figure 1 shows the framework of the SOWA method created in this research.

SOWA METHOD FRAMEWORK

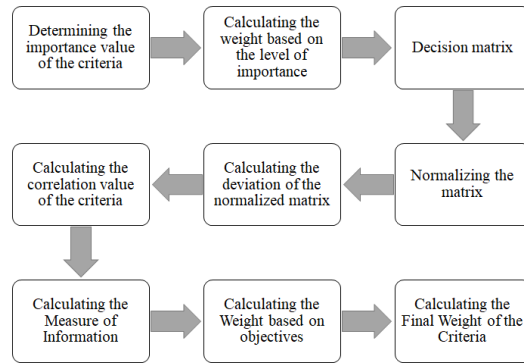


Fig. 1. SOWA Method Framework.

The first stage in the SOWA method is to determine the importance value of each criterion, which involves assessing the relative importance level of each criterion based on the views of experts or decision-makers[39,40]. This value is assigned on a specific scale based on subjective perception using the scale presented in Table 1.

Table 1. Scale of the Importance Level of the Criteria.

Score	Level of Importance	Description
0.1	Very Unimportant	This criterion hardly influences the decision-making process.
0.2	Not Important	This criterion has a small influence and can be ignored in many cases.
0.3	Somewhat Unimportant	This criterion is relevant, but rarely becomes the main determining factor.
0.4	Less Important	This criterion is beginning to be considered in some cases, but it is not a priority.
0.5	Neutral	This criterion has a moderate influence and is considered quite important.
0.6	Quite Important	This criterion has a significant contribution to the assessment.
0.7	Important	This criterion is often considered in decision-making.
0.8	Very Important	This criterion greatly influences the decision and should not be overlooked.
0.9	Almost Very Important	This criterion is almost always a primary consideration.
1.0	Absolutely Important	This criterion is a key factor and greatly determines the outcome of the decision.

Scoring is carried out through controlled expert judgment, where experts are asked to evaluate the importance level of each criterion based on their experience and the context of the problem, referring directly to the pre-established scale definitions. This approach serves as a mechanism to control cognitive bias, as experts do not evaluate freely but within the boundaries of a uniform and documented scale. Additionally, the process of aggregating assessments is conducted through weight normalization, so that extreme differences between evaluators can be minimized and the final weights remain in a stable proportion.

The second stage in the SOWA method is to determine weights based on the levels of importance obtained in the previous step, which are converted into subjective weights. The calculation of the criteria weights based on the level of importance is done using the following equation.

$$w_j^{sub} = \frac{r_i}{\sum_{j=1}^n r_j} \quad (1)$$

The third stage in the SOWA method is to compile a decision matrix that contains the performance values of alternatives against each criterion. Each row represents an alternative, and each column represents a criterion. The decision matrix is created using the following equation.

$$X = \begin{bmatrix} x_{i1} & \cdots & x_{in} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \quad (2)$$

The fourth stage in the SOWA method is the normalization of the decision matrix, which aims to equalize the assessment scale among criteria so that they can be compared fairly. The normalization of the decision matrix is calculated using the following equation.

$$r_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \quad (3)$$

The fifth stage in the SOWA method is to calculate the deviations of the normalized matrix to determine the level of variation or inequality of values among alternatives in each criterion. The deviation values of the normalized matrix are calculated using the following equation.

$$\sigma_j = \sqrt{\frac{(\sum_{i=1}^m r_{ij} - \bar{r}_j)^2}{m-1}} \quad (4)$$

The sixth stage in the SOWA method is to calculate the correlation values among criteria to take into account both deviations and independencies among criteria. The correlation values among criteria are calculated using the following equation.

$$d_{ij} = \frac{\sum_{i=1}^n (r_{ij} - \bar{r}_j) - (r_{ij} - \bar{r}_h)}{\sqrt{\sum_{i=1}^n (r_{ij} - \bar{r}_j)^2} * \sqrt{\sum_{i=1}^n (r_{ij} - \bar{r}_h)^2}} \quad (5)$$

The seventh stage in the SOWA method is calculating the measure of information to account for the size of the information obtained by combining deviation and correlation. The measure of information is calculated using the following equation.

$$c_j = \sigma_j * \left(\sum_{j=1}^n (1 - d_{ij}) \right) \quad (6)$$

The eighth stage in the SOWA method is to calculate weights based on objective data to assess the weights of criteria based on the value of the measure of information. The weight value based on objective data is calculated using the following equation.

$$w_j^{obj} = \frac{c_j}{\sum_{j=1}^n c_j} \quad (7)$$

The ninth stage in the SOWA method is calculating the final weight of the criteria obtained by combining subjective and objective weights using the average of the results. The weight value of the criteria is calculated using the following equation.

$$w_j^{final} = \frac{w_j^{sub} + w_j^{obj}}{2} \quad (8)$$

The final result of the entire process in the SOWA method stages is the final weight of each criterion obtained from the combined subjective and objective weights proportionally, taking into account the importance level of the criteria and statistical information from actual data.

The SOWA method combines subjective and objective weights in multi-criteria decision-making with the aim of integrating decision-makers' preferences with factual information contained in the data. Subjective weights represent expert judgment, experience, and strategic priorities, while objective weights are calculated based on data characteristics such as variation, dispersion, or the level of information among criteria. The combination of these two types of weights allows for a balance between human intuition and empirical evidence, reducing subjective bias while also avoiding pure data dominance that could overlook the decision context. With this combinative approach, the resulting criterion weights become more stable, representative, and adaptive to the complexity of real-world problems, especially in decision support systems involving multiple criteria and interests.

2.2. Implementation of the SOWA Method

The implementation of the SOWA Method Framework is a strategic step in the development of decision support systems based on a systematic and structured approach. The SOWA method is designed to integrate the process of weighting criteria that often tends to be subjective by incorporating the principles of objectivity, consistency, and transparency. By using this framework, the assessment process in decision-making becomes more rational and accountable, especially in complex multi-criteria environments. The stages of SOWA method implementation are shown

in Figure 2.

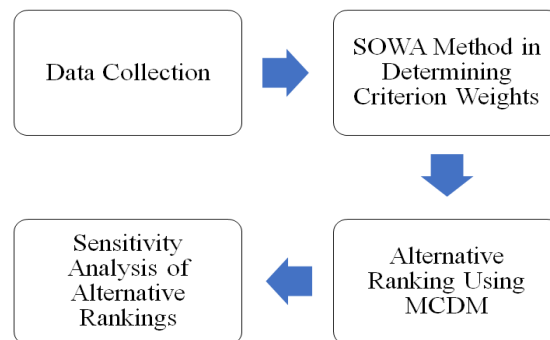


Fig. 2. Implementation of the SOWA Method Framework.

The implementation of the SOWA method begins with the data collection stage, where information is gathered regarding the relevant criteria and alternatives according to the decision-making context. After the data is collected, the next stage is determining the criteria weights using the SOWA method. At this stage, the SOWA method is applied to calculate the weights by combining the subjective and objective concepts of each criterion based on the variation and distribution of data, thus avoiding subjective bias in the assessment. Next, alternative ranking is performed using the MCDM method (Alternative Ranking Using MCDM), utilizing the criterion weights that have been calculated through SOWA. The final stage is sensitivity analysis to evaluate how stable the alternative ranking results are against changes in the criterion weights. This analysis is important to ensure that the decisions made remain consistent even amidst fluctuations or uncertainties in the input data.

3. Results and Discussion

The SOWA method framework presents itself as a new algorithm designed to balance the weighting of criteria in a fairer and more accurate manner through a hybrid approach that combines subjective and objective assessments. In multi-criteria decision-making, the imbalance of criterion weights often becomes a source of inaccuracies in the final results, especially when relying solely on one approach, either subjective, which is prone to bias, or objective, which is insensitive to context. By integrating the strengths of both, SOWA provides a systematic solution that considers not only the perceptions of experts or users but also the characteristics of the data that can be measured mathematically. This framework is designed to enhance the reliability of decision support systems across various fields, from strategic management and performance evaluation to alternative selection in the business and technology world.

3.1. Data Collection

The collection of accurate and representative data is very important because the quality of this data will directly affect the final results of the weighting of criteria and the ranking of alternatives produced in the subsequent stages. Therefore, the data collection process must be conducted systematically and thoroughly to ensure that all relevant factors have been considered. In this study, the data used is secondary data from research in determining the selection of employee admission[41]; the data used is displayed in Table 2.

Table 2. Employee Recruitment Selection Data.

Candidate Name	Criteria Code					
	K1	K2	K3	K4	K5	K6
Candidate 1	4	5	85	90	8	4
Candidate 2	3	3	75	80	7	3
Candidate 3	5	7	90	95	9	5
Candidate 4	4	4	70	85	6	3
Candidate 5	3	2	60	70	5	2
Candidate 6	5	6	80	92	9	4
Candidate 7	4	4	78	88	8	4
Candidate 8	2	1	50	65	4	2
Candidate 9	4	5	80	89	7	5
Candidate 10	3	3	65	75	6	3

Data collection is a crucial stage in the implementation of the SOWA method necessary for the decision-making

process; data are collected carefully from various relevant sources. This process involves gathering information regarding the criteria that will be used in the assessment and the alternatives that will be evaluated.

3.2. SOWA Method in Determining Criteria Weighting

The SOWA Method in Determining Criteria Weighting is a key stage in the application of the SOWA Method Framework, which aims to calculate criteria weights objectively and evenly by combining subjective and objective approaches. This process integrates both approaches in a structured manner, where the subjective weights assigned by experts are adjusted and refined by the results of more mathematical objective analysis. By using certain techniques, the criteria weights can be determined more objectively without disregarding possibly relevant subjective viewpoints. The final result of this process is a more balanced and accurate weight of criteria that reflects the importance of each criterion in the context of the decision-making being carried out. This SOWA Method ensures that the weighting of criteria is not solely based on assumptions or preferences of one party but is also supported by relevant and factual data.

The first stage in the SOWA method is to determine the importance value of each criterion used based on the scale of the importance level of the criteria found in Table 1, with the resulting importance values presented in Table 3.

Table 3. Importance Values of the Criteria.

Criteria	Score
Education (K1)	0.6
Work Experience (K2)	1
Creativeness (K3)	0.5
English Language Proficiency (K4)	0.4
Technical Skills (K5)	0.7
Leadership (K6)	0.8

The importance value of the criteria for employee recruitment selection is obtained from the Human Resource Development department, which represents a professional perspective on the extent to which each criterion contributes to the effectiveness of decision-making. This value is given based on the HRD's experience, intuition, and deep understanding of the organization's needs.

The second stage in the SOWA method is to determine the weights based on the level of importance obtained in the previous step, which is transformed into subjective weights. The calculation of criterion weights based on the level of importance is carried out using (1), and the results of the weight calculations are displayed in table 4.

Table 4. Weight Results Based on The Importance Value of the Criteria.

Criteria	w_j^{sub}
Education (K1)	0.15
Work Experience (K2)	0.25
Creativeness (K3)	0.125
English Language Proficiency (K4)	0.1
Technical Skills (K5)	0.175
Leadership (K6)	0.2

The third stage in the SOWA method is to compile a decision matrix that contains the performance values of alternatives against each criterion. Each row represents one alternative, and each column represents one criterion. The decision matrix is created using (2), and the general form of the decision matrix is as follows.

$$X = \begin{bmatrix} x_{11} & x_{21} & x_{31} & x_{41} & x_{51} & x_{61} \\ x_{12} & x_{22} & x_{32} & x_{42} & x_{52} & x_{62} \\ x_{13} & x_{23} & x_{33} & x_{43} & x_{53} & x_{63} \\ x_{14} & x_{24} & x_{34} & x_{44} & x_{54} & x_{64} \\ x_{15} & x_{25} & x_{35} & x_{45} & x_{55} & x_{65} \\ x_{16} & x_{26} & x_{36} & x_{46} & x_{56} & x_{66} \\ x_{17} & x_{27} & x_{37} & x_{47} & x_{57} & x_{67} \\ x_{18} & x_{28} & x_{38} & x_{48} & x_{58} & x_{68} \\ x_{19} & x_{29} & x_{39} & x_{49} & x_{59} & x_{69} \\ x_{110} & x_{210} & x_{310} & x_{410} & x_{510} & x_{610} \end{bmatrix}$$

The results of the decision matrix from the assessment data in Table 2 are as follows.

$$X = \begin{bmatrix} 4 & 5 & 85 & 90 & 8 & 4 \\ 3 & 3 & 75 & 80 & 6 & 3 \\ 5 & 7 & 90 & 95 & 9 & 5 \\ 4 & 4 & 70 & 85 & 6 & 3 \\ 3 & 2 & 60 & 70 & 5 & 2 \\ 5 & 6 & 80 & 92 & 9 & 4 \\ 4 & 4 & 78 & 88 & 8 & 4 \\ 2 & 1 & 50 & 65 & 4 & 2 \\ 4 & 5 & 80 & 89 & 7 & 5 \\ 3 & 3 & 65 & 75 & 6 & 3 \end{bmatrix}$$

The fourth stage in the SOWA method is the normalization of the decision matrix, which aims to equalize the assessment scale among criteria so that they can be fairly compared. The results of the normalization calculation of the decision matrix are presented in Table 5.

Table 5. Normalization of the Decision Matrix.

Candidate Name	Criteria Code					
	K1	K2	K3	K4	K5	K6
Candidate 1	0.6667	0.6667	0.8750	0.8333	0.8000	0.6667
Candidate 2	0.3333	0.3333	0.6250	0.5000	0.6000	0.3333
Candidate 3	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Candidate 4	0.6667	0.5000	0.5000	0.6667	0.4000	0.3333
Candidate 5	0.3333	0.1667	0.2500	0.1667	0.2000	0.0000
Candidate 6	1.0000	0.8333	0.7500	0.9000	1.0000	0.6667
Candidate 7	0.6667	0.5000	0.7000	0.7667	0.8000	0.6667
Candidate 8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Candidate 9	0.6667	0.6667	0.7500	0.8000	0.6000	1.0000
Candidate 10	0.3333	0.3333	0.3750	0.3333	0.4000	0.3333

The fifth stage in the SOWA method is to calculate the deviation of the normalized matrix to determine the level of variation or inequality of values among alternatives for each criterion, calculated using (4); the results of the deviation calculations of the normalized matrix are displayed in Table 6.

Table 6. Deviation of the Normalized Matrix (values to be recalculated using Eq. (4)).

Deviation Value	Criteria Code					
	K1	K2	K3	K4	K5	K6
σ_j	0.150	0.289	0.006	0.005	0.079	0.171

The sixth stage in the SOWA method is to calculate the correlation values between criteria to account for deviations and independence between criteria, which are calculated using (5). The results of the calculation of correlation values between criteria are displayed in table 7.

Table 7. Correlation Values Between Criteria.

	K1	K2	K3	K4	K5	K6
K1	1.0000	0.9623	0.8661	0.9426	0.8943	0.8133
K2	0.9623	1.0000	0.9261	0.9590	0.9147	0.9015
K3	0.8661	0.9261	1.0000	0.9601	0.9413	0.9012
K4	0.9426	0.9590	0.9601	1.0000	0.9320	0.9079
K5	0.8943	0.9147	0.9413	0.9320	1.0000	0.8349
K6	0.8133	0.9015	0.9012	0.9079	0.8349	1.0000

The seventh stage in the SOWA method is to calculate the size of the information to account for the information size obtained by combining the deviation and correlation calculated using (6); the results of the information size calculations are shown in Table 8.

Table 8. Measure of Information Value.

Measure of Information Value	Criteria Code					
	K1	K2	K3	K4	K5	K6
c_j	0.0782	0.0971	0.0023	0.0015	0.0381	0.1095

The eighth stage in the SOWA method is to calculate the weights based on objective data to assess the weights of the criteria based on the information measure values calculated using (7); the results of the objective criterion weight calculations are displayed in Table 9.

Table 9. Objective Weight Results.

Weighting Value	Criteria Code					
	K1	K2	K3	K4	K5	K6
w_j^{obj}	0.2394	0.2973	0.0072	0.0045	0.1166	0.3351

The ninth stage in the SOWA method is to calculate the final weight of the criteria obtained by combining subjective and objective weights using the average result calculated using (8). The results of the final objective weight calculation of the criteria are shown in Table 10.

Table 10. Final Weight Results of the SOWA Method.

Weighting Value	Criteria Code					
	K1	K2	K3	K4	K5	K6
w_j	0.1947	0.2736	0.0661	0.0522	0.1458	0.2676

The results of the weighting using the SOWA Method yield a distribution of criterion weights that indicate the relative importance level of each factor in the decision-making process. The criterion Work Experience (K2) occupies the highest position with a weight of 0.2736, reflecting that work experience is considered the most crucial aspect by decision-makers, particularly HRD, in evaluating candidates. This is followed by Leadership (K6) with a weight of 0.2676, indicating the importance of leadership skills in the assessed role. The criterion Education (K1) also has a significant weight of 0.1947, indicating that educational background remains an important consideration. Meanwhile, Technical Skills (K5) receives a weight of 0.1458, indicating that technical skills are considered quite important but still below leadership and work experience. On the other hand, criteria such as Creativeness (K3) and English Language Proficiency (K4) received lower weights of 0.0661 and 0.0522, respectively, suggesting that although these factors are taken into account, their influence on decision-making is relatively small. This result reflects a balanced approach of the SOWA Method that combines the subjective assessment of HRD with objective data, thus producing criteria weights that comprehensively reflect the actual needs of the organization.

3.3. Alternative Ranking Using MCDM

The combination of the SOWA method with various MCDM methods is a strategic approach aimed at improving the accuracy and fairness of the multi-criteria decision-making process. SOWA plays a role in determining the criteria weights in a more balanced manner by combining the subjective and objective approaches. The final result of the SOWA method produces criteria weights that objectively represent the organization's priorities while remaining consistent with actual conditions observed in the field. After the criteria weights are determined by the SOWA method, these weights are then used in various MCDM methods to rank alternatives. MCDM methods such as Simple Additive Weighting (SAW), Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA), Grey Relational Analysis (GRA), Multi-Attribute Utility Theory (MAUT), Weighted Aggregated Sum Product Assessment (WASPAS), Weighted Product (WP), Simple Multi-Attribute Rating Technique (SMART), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Multi-Attributive Border Approximation Area Comparison (MABAC), and Multi-Attributive Ideal-Real Comparative Analysis (MAIRCA) have different algorithms for assessing and ranking alternatives based on weighted criteria. With weights derived from SOWA, the alternative evaluation process becomes fairer, more relevant, and reflects a comprehensive priority. The ranking results of alternatives from various methods are presented in Table 11.

Table 11. Ranking of Alternatives.

Candidate Name	Rank MCDM									
	SAW	MOORA	GRA	MAUT	WASPAS	WP	SMART	TOPSIS	MABAC	MAIRCA
Candidate 3	1	1	1	1	1	1	1	1	1	1
Candidate 6	2	2	2	2	2	2	2	2	2	2
Candidate 9	3	3	3	3	3	3	3	3	3	3
Candidate 1	4	4	4	4	4	4	4	4	4	4
Candidate 7	5	5	5	5	5	5	5	5	5	5
Candidate 4	6	6	6	6	6	6	6	6	6	6
Candidate 2	7	7	7	7	7	7	7	7	7	7
Candidate 10	8	8	8	8	8	8	8	8	8	8
Candidate 5	9	9	9	9	9	9	9	9	9	9
Candidate 8	10	10	10	10	10	10	10	10	10	10

The results of the integration between weighting using the SOWA method and alternative evaluation with ten Multi-Criteria Decision Making (MCDM) methods showed a very consistent ranking across the methods. Among the ten assessed candidates, Candidate 3 ranked first absolutely in all MCDM methods, from SAW, MOORA, GRA, MAUT, WASPAS, WP, SMART, TOPSIS, MABAC, to MAIRCA. The consistency of this ranking indicates that the candidate has outstanding performance across all major criteria, especially those with high weights such as Work Experience and Leadership according to the SOWA method. The second position is consistently occupied by Candidate 6, followed by Candidate 9 in third place, and so on until Candidate 8 who ranks last across all methods. The alignment of results across methods suggests that the criterion weights determined by the SOWA method have produced a stable and objective score distribution, thereby reinforcing the reliability of the decision-making system established. It also confirms that the combination of SOWA with various MCDM methods is capable of producing valid, accurate, and minimally biased final results.

3.4. Sensitivity Analysis of Alternative Rankings

Sensitivity analysis is conducted to examine how the stability of alternative rankings is influenced by changes in the weights of criteria used in the decision-making process. In this context, the initial weights are obtained through the SOWA method, which combines subjective and objective assessments in determining the importance of each criterion. Then, these weights are modified proportionally in different scenarios to observe their impact on the ranking order produced by MCDM methods such as SAW, TOPSIS, MOORA, GRA, and others.

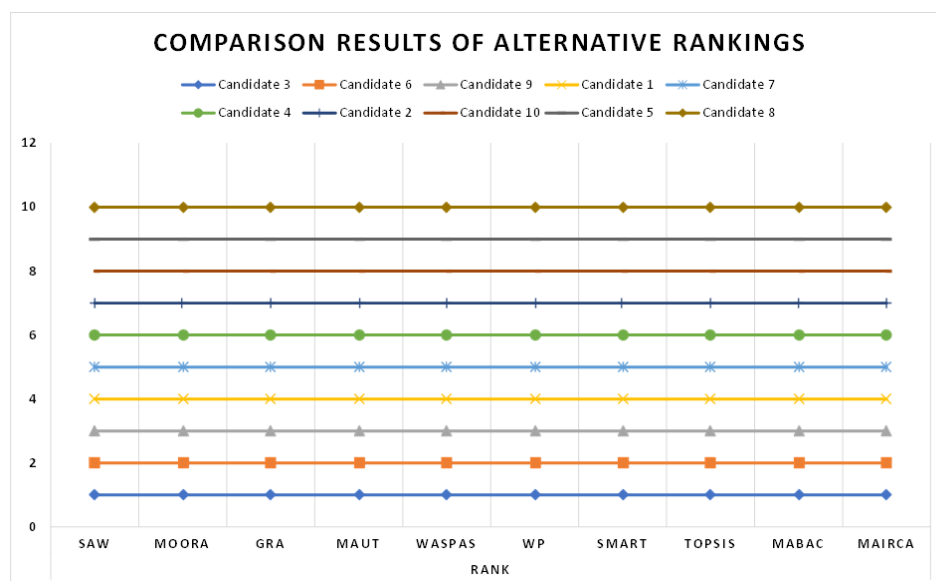


Fig. 3. Comparison Results of Alternative Rankings.

The results of the analysis show that the rankings of the top three candidates (Candidate 3, 6, and 9) remain stable across varying weight scenarios, indicating that these alternatives perform well and consistently against the most influential criteria, such as Work Experience (K2) and Leadership (K6). Meanwhile, some candidates in the middle and lower positions experience slight ranking shifts when there are increases or decreases in weights on highly sensitive criteria, such as Technical Skills (K5) and Creativeness (K3). Thus, this sensitivity analysis proves that the assessment system built based on weights from the SOWA method is relatively resilient to fluctuations, especially for the highest rankings. This strengthens the assurance that the ranking results produced by this system can be relied upon in dynamic conditions, as well as being capable of providing consistent and stable recommendations in multi-criteria decision-making.

The comparison of weighting methods was conducted involving SOWA, Entropy, MEREC, and CRITIC to assess the characteristics of the weights generated by each approach. The Entropy method emphasizes the variation of data information, so criteria with higher levels of uncertainty receive greater weights, while CRITIC considers a combination of data dispersion and inter-criteria conflict through correlation analysis. MEREC assesses the importance of criteria based on their influence on changes in aggregate results when a criterion is removed, thereby highlighting the structural contribution of each criterion within the decision-making system. Meanwhile, SOWA integrates the results of objective weighting with expert assessments through a controlled balancing mechanism, so that the final weights not only reflect the characteristics of the data but also the contextual relevance of the criteria. With this comparison, differences in weight patterns and their implications for the stability and interpretability of the ranking results can be observed. The results of the criteria weight comparison are presented in Table 12.

Table 12. Comparison Results of Criteria Weights.

Method	Criteria Code					
	K1	K2	K3	K4	K5	K6
Entropy	0.1377	0.4558	0.0575	0.0302	0.1218	0.1969
SOWA	0.1947	0.2736	0.0661	0.0522	0.1458	0.2676
MEREC	0.1974	0.1573	0.1231	0.1881	0.1643	0.1697
CRITIC	0.1675	0.1253	0.1481	0.1220	0.1964	0.2406

Table 12 shows the differences in the distribution of criterion weights generated by the Entropy, SOWA, MEREC, and CRITIC methods, reflecting the characteristics of each weighting approach. The Entropy method assigns a dominant weight to criterion K2, indicating that this criterion has the highest level of information variation in the data, while other criteria receive relatively small weights. In contrast, SOWA produces a more balanced weight distribution, with emphasis on K6 and K2, indicating an effort to balance the data characteristics and the contextual relevance of the criteria. The MEREC method shows relatively even weights across all criteria, reflecting an assessment based on the structural contribution of each criterion to the aggregate result. Meanwhile, CRITIC places the highest weights on K6 and K5, indicating a combination of data dispersion and the level of conflict between criteria. This difference in weight patterns shows that each method has a different evaluative perspective on the importance of criteria, which ultimately can affect the stability and interpretation of ranking results.

The results of the analysis and comparison of the weighting methods conducted indicate that each approach—Entropy, MEREC, CRITIC, and SOWA—has different characteristics and evaluative focuses in representing the importance level of criteria. The Entropy method tends to highlight criteria with the highest data variation, MEREC emphasizes the structural contribution of criteria to the aggregate outcome, and CRITIC considers data dispersion as well as inter-criteria relationships. Meanwhile, SOWA is capable of producing a more balanced weight distribution by integrating data information and contextual considerations, thus providing weights that are more stable and easier to interpret. These findings suggest that the SOWA approach has the potential to be a relevant alternative in multi-criteria decision support systems, especially when a balance is needed between data characteristics and criterion relevance in decision-making contexts.

3.5. Discussion

The combination of the SOWA method and ten MCDM methods shows very strong consistency in the ranking process of alternatives. Candidate 3 consistently occupies the first position across all methods, indicating that this candidate has a dominant advantage in the criteria with the highest weights such as Work Experience and Leadership, as produced by the SOWA method. This consistency not only affirms the effectiveness of the weights generated by SOWA but also reflects that the MCDM methods used are capable of evaluating alternatives in alignment with those weights.

Furthermore, through sensitivity analysis, this decision-making system has proven to be stable against changes in weights. When the weights of the criteria were modified, particularly for criteria with medium to high impact, the top three rankings remained unchanged, while the middle and lower rankings experienced insignificant fluctuations. This reinforces that the SOWA method can produce weights that are not only fair and representative but also robust against the dynamics of priorities that may occur in real decision-making. Thus, the combination of SOWA and MCDM methods not only provides valid and objective final results but also enhances the reliability of the system in various scenarios.

4. Conclusion

The SOWA method is a new approach that can unify two important perspectives in determining criterion weights, namely the subjective assessment from experts and objective measurement based on data. The implementation results of this method indicate that SOWA is capable of producing criterion weights that are more balanced and fair, and that represent the real interests of each evaluation aspect. The strength of SOWA lies in its flexibility to accommodate expert preferences without neglecting the validity of quantitative data. The final weights produced by this method also prove to be stable and effective when used in multi-criteria evaluation processes, and yield consistent alternative ranking results when combined with various MCDM methods. Therefore, SOWA is a robust, reliable weighting method that is suitable for application in decision support systems across various fields.

All the Declarations and Statements

Author Contributions Statement

Sumanto – Methodology, The Concept of the Proposed Method, and Writing – Review and Editing; Involved in the

preparation of research methodology, the design and development of proposed method concepts, as well as writing, reviewing, and thoroughly editing manuscripts.

Aditya Lapu Kalua – Data preparation, Implementation Method, Writing – Drafted the initial manuscript: Involved in the preparation and processing of data, the implementation of methods used in the research, as well as the drafting of the initial manuscript.

Fintri Indriyani – Literature Review, Visualization, and Writing – Drafted the initial manuscript: Involved in relevant literature review, preparation of data visualizations or models, as well as writing and drafting the initial manuscript.

Rakhmadi Irfansyah Putra – Conceptualization, Implementation Method, Writing – Drafted the initial manuscript: Involved in the conceptualization of the research, the implementation of the methods used, as well as the writing and preparation of the initial draft of the manuscript.

Ayuni Asistiyasari – Data preparation, Implementation Method, The Concept of the Proposed Method: Involved in the preparation and processing of data, implementation of research methods, as well as formulation and development of the proposed method concepts.

Adhie Thyo Priandika – The Concept of the Proposed Method, Sensitivity Analysis, Statistical Analysis, Writing – Review and Editing: Involved in the formulation and development of the proposed method concept, conducting sensitivity and statistical analyses, as well as reviewing and editing manuscripts.

All authors have read and agreed to the published version of the manuscript.

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The authors declare no conflicts of interest.

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The data used to support the findings of this study are available from the corresponding author upon request.

Ethical Declarations

The authors declare that this article does not contain any studies with human participants or animals performed by any of the authors.

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Declaration of Generative AI in Scholarly Writing

The authors used generative AI to improve the writing clarity of this paper. They reviewed and edited the AI-assisted content and take full responsibility for the final publication.

Abbreviations

The following abbreviations are used in this manuscript:

CRITIC – Criteria Importance Through Intercriteria Correlation

GRA – Grey Relational Analysis

MABAC – Multi-Attributive Border Approximation Area Comparison

MAIRCA – Multi-Attributive Ideal-Real Comparative Analysis

MCDM – Multi-Criteria Decision Making

MAUT – Multi-Attribute Utility Theory

MEREC – Method based on the Removal Effects of Criteria

MOORA – Multi-Objective Optimization on the basis of Ratio Analysis

SAW – Simple Additive Weighting

SMART – Simple Multi-Attribute Rating Technique

SOWA – Subjective and Objective Weighting Approach

TOPSIS – Technique for Order Preference by Similarity to Ideal Solution

WASPAS – Weighted Aggregated Sum Product Assessment

WP – Weighted Product

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